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Shape index distribution based local surface complexity applied to the human cortex

Sun Hyung Kim^a, Vladimir Fonov^b, D. Louis Collins^b, Guido Gerig^c, The IBIS Network, and Martin A. Styner^{a,b}

^aDepartment of Psychiatry, University of North Carolina at Chapel Hill, USA

^bMcConnell Brain Imaging Center, Montreal Neurological Institute, Montreal, QC, Canada

^cScientific Computing and Imaging Institute, University of Utah, Salt Lake City, USA

^dDepartment of Computer Science, University of North Carolina at Chapel Hill, USA

Abstract

The quantification of local surface complexity in the human cortex has shown to be of interest in investigating population differences as well as developmental changes in neurodegenerative or neurodevelopment diseases. We propose a novel assessment method that represents local complexity as the difference between the observed distributions of local surface topology to its best-fit basic topology model within a given local neighborhood. This distribution difference is estimated via Earth Move Distance (EMD) over the histogram within the local neighborhood of the surface topology quantified via the Shape Index (SI) measure. The EMD scores have a range from simple complexity (0.0), which indicates a consistent local surface topology, up to high complexity (1.0), which indicates a highly variable local surface topology. The basic topology models are categorized as 9 geometric situation modeling situations such as crowns, ridges and fundi of cortical gyro and sulci. We apply a geodesic kernel to calculate the local SI histogram distribution within a given region. In our experiments, we obtained the results of local complexity that shows generally higher complexity in the gyral/sulcal wall regions and lower complexity in some gyral ridges and lowest complexity in sulcal fundus areas. In addition, we show expected, preliminary results of increased surface complexity across most of the cortical surface within the first years of postnatal life, hypothesized to be due to the changes such as development of sulcal pits.

Keywords

Local Shape Complexity Index; Shape Index; Earth Move Distance

1. INTRODUCTION

The cerebral cortex is a highly folded, convoluted object composed of sulci and gyri. Folding is apparent from approximately 25 week of gestational age with changes expected throughout early postnatal development.¹ Cortical complexity would be related to neurons and their connections being packed into the limited intra-cranial space and is associated with

advanced higher intelligence.² Hence, quantification of complexity is of high interest in investigations of brain functional and anatomical development.

Historically older measurements of cortical complexity include the global gyrification index (GI) that is defined as the area ratio between outer cortical surface such as cerebral hull surface and the cortical gray matter surface. GI has been widely used to investigate the global complexity.³ GI measurements are global and scale invariant, thus generally do not yield localized measures of complexity. Another complexity measurement is the fractal dimension that has a score 1 for lines, 2 for sets describing surface.⁴ It has an advantage to calculate surface complexity without the need of a reference surface such as cerebral hull, but the representative score of fractal dimension is very sensitive to surface noise.

More recently, local gyrification has been estimated using surface intrinsic or extrinsic curvature at each geometric position that is thousands of vertexes over the entire gray or white surface.^{5, 6} While the extrinsic curvature or mean curvature is a fundamental measurement for sulcal folding or complexity, the tangential expansion of cortex can be explained using the intrinsic curvature or Gaussian curvature that quantifies a mount of the excessive area as compared to a plane within the nearest neighbor points of the surface. Local measures of GI or complexity have been proposed using local kernels such as spherical windows⁴ or N-ring neighborhood vertexes.⁷ The region of interest (ROI) was defined using intersected points between outer surface and sphere with a constant radius or the number of neighborhood and delineated corresponded perimeter of pial surface. However, local GI measures need relatively large kernel or N-ring radius (commonly larger than 10 mm) in order to compute complexity over a larger region or cortical lobe. Smaller radius settings lead a significant loss of measurement sensitivity.

In this work, we aim to develop a fine-scale measurement of cortical surface complexity that is an appropriately insensible to surface noise, invariant to brain size and directly measureable on surface points without the need of reference surfaces. For that we propose a novel local complexity measure employing localized, small geodesic kernel applied to the intermediate cortical surface (in-between the white and pial cortical surfaces). Its scale can be considered in between the very fine scale of intrinsic curvature analysis and the coarse scale of local GI measures.

2. METHOD

2.1 Data

We used images from 27 MRI scans from 9 typically developing subjects assessed at 6, 12 and 24 month available as part of the IBIS (Infant Brain Imaging Study) network acquired at 4 different sites, each equipped with 3T Siemens Tim Trio scanners. The scan sessions included T1 weighted (160 slices with TR=2400ms, TE=3.16ms, flip angle=8, field of view 224×256) and T2 weighted (160 slices with TR=3200ms, TE=499ms, flip angle=120, field of view 256×256) MR scans. All datasets possess the same spatial resolution of $1 \times 1 \times 1\text{mm}^3$.

2.2 Image Processing

The raw MR T1- and T2-weighted images were first separately corrected for geometric distortions⁸ as well as intensity non-uniformity.⁹ All T2-weighted images were rigidly registered to the corresponding T1-weighted images via mutual information registration. For cases where the automatic co-registration failed we manually initialized the registration procedure. Then both T1 and T2 were transformed to stereotaxic space based on the registration of the T1 scan.¹⁰ An intensity growth map (IGM) based method was applied to the T1w and T2w images of 12 month old subjects to enhance the contrast WM/GM boundary due to under-myelination region.¹¹ Atlas-Based Classification (ABC)¹² was then applied to compute a further inhomogeneity correction and classify images into white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). Finally inner- and outer surface models were extracted using an adapted version of the 'Constrained Laplacian-Based Automated Segmentation with Proximities (CLASP)' pipeline.¹³ The surfaces for 6 month data were generated by propagating surfaces computed from 12 month old data via deformable multi-modal within-subjects co-registration¹⁴ of MRI data from 12 month to 6 month images. The cortical surface model consisted of 81,920 high-resolution triangle meshes (40,962 vertices) in each hemisphere, and the smoothed middle surface was obtained by averaging pial and white surfaces, followed by a single iteration of one-neighborhood averaging based surface soothing. Cortical surface correspondence was established via spherical registration to an average surface template, which performs a sphere-to-sphere warping by matching crowns of gyri.¹⁵

2.3 Calculating Local Complexity

The well-known surface shape index (SI) is calculated on each points of the surface for use as local surface complexity employing the following equation: $SI_i = (2/\pi) * \arctan((\kappa_{2,i} + \kappa_{1,i})/(\kappa_{2,i} - \kappa_{1,i}))$, where i is the vertex index, κ_1 and κ_2 are the principal curvatures on surface model. The SI score ranges from -1 to 1 with 9 geometric topological situations at the following values: spherical cup ($SI = -1.0$), cup/trough ($SI = -0.75$), rut ($SI = -0.5$), saddle rut ($SI = -0.25$), saddle ($SI = 0$), saddle ridge ($SI = 0.25$), ridge ($SI = 0.5$), dome ($SI = 0.75$), spherical dome ($SI = 1.0$) (Figure 1, b). The proposed local shape complexity index (SCI) was defined by the quantification of SI variance within a local region. For example, as illustrated in Figure 1, the regions that have the homogeneous SIs as in the bottom of ear or nose area have a very low complexity, regions that have both the convex and concave forms such as round the neck or ear, on the other hand, have a relatively high complexity. We used the discrete Earth Mover's Distance (EMD) to calculate the difference of the actual local SI distribution measured via a local histogram to the best fitting, idealized histogram of the 9 topological geometric settings mentioned above. The EMD represents a metric that captures the minimal cost that must be paid to transform one distribution into the other via linear optimization.¹⁶

Let $P_v = \{p_1, p_2, \dots, p_n\}$ be the histogram of SI distribution with n bin, where p_n is the number that is representative for each bin and v is vertex index. Let $Q_s = \{q_1, q_2, \dots, q_9\}$ be the histograms of the 9 basic geometric settings.

$$EMD(P, Q) = \frac{\sum_{i=1}^n \sum_{j=1}^n d_{ij} f_{ij}}{\sum_{i=1}^n \sum_{j=1}^n f_{ij}}$$

$$Local\ Complexity_{\nu} = \min(EMD(P_{\nu}, Q_s))$$

Where f_{ij} is the flow between p_i and q_j , and the ground distance d_{ij} is calculated by the norm between two bins. The range of EMD is from 0 to 1.0, simple to complex (Figure 1, c). The EMD at each vertex is computed for all 9 basic settings and the minimal EMD at each vertex is chosen as its complexity measure. This measure of complexity is relatively sensitive to the choice of the kernel size employed to compute the local SI histogram. Figure 2 illustrates the size of local geodesic kernels at various (randomly sampled) cortical locations. For a kernel size over 5mm, several cortical locations would sample both gyral ridges as well sulcal fundi. In this work, we made the decision to employ a kernel size that does not cover both sulci and gyri with the same kernel regions. Given the visualization in Figure 2, we empirically chose 3mm as the kernel size of choice here. Larger kernel sizes would be certainly "valid" too, and would simply capture a different scale of cortical shape complexity.

3. RESULTS

3.1 Kernel Size

The meshes representing cortical surface that are generated by CIVET have several connecting neighbor vertex. The space of subsequent neighboring triangles followed two-dimensional Riemann space. The geodesic distance, therefore, is more accurate to set a radius threshold as kernel size than Euclidian distance. Different kernel sizes would be expected to yield different results with differing biological interpretations. Figure 3 shows the calculated SCIs with different geodesic kernel size in a randomly selected 6 month dataset. SCIs that are calculated with small kernel size, 2.5mm, tend to show mainly simple complexity and those of with kernel size over 3.5mm show relatively high complexity across the surface (see Figure 3 a). Employing a heat kernel smoothing operator, as is commonly used in cortical data smoothing prior to analysis, we see that this effects can be seen even more pronounced (Figure 3 b).

3.2 Local shape complexity

Figure 4 shows two examples of the local complexity measure alongside their local SI histogram distribution and the idealized histogram of its corresponding best fitting basic geometry setting. In this particular example, the selected gyral area is more complex than selected sulcal area as indicated by the higher EMD distance/SCI value. In Figure 5, the average local complexity measured across all 9 subjects is visualized on the full brain at the 3 ages 6 months, 12 months and 24 months. Overall the patterns at the three ages look quite similar. Wide sulcal fundus regions display the lowest levels of local complexity, whereas

several gyral wall and gyral ridge regions display the highest levels of complexity. Gyral saddle regions and wide gyral ridges display more intermediate complexity.

While the pattern of cortical complexity is largely stable in the 3 ages studied here, several regions do show preliminary results of change across time. Overall local brain shape seems to become more complex over the time in superior frontal, post-/pre-central and superior temporal area in Figure. 5. The sulcal fundus area seems to become more complex, visible especially in the prefrontal and occipital lobes. This is likely due to the development of sulcal pits or the decrease in width of the sulcal fundus as seen in the superior temporal sulcus.

As concave cup and convex dome regions are located at the opposite extremes of the SI scale, locations that encompass both near sulcal to near gyral situations within the small neighborhood of the geodesic kernel were expected to show largest complexity as can be seen in these results. In contrast, locations at deep sulci close to saddle region were expected to show lower complexity, which was also observed in this study. With respect to longitudinal change, a narrowing of the sulcal fundus would result in increased complexity. A new sulcal pits or a change in the sulcal/gyral pattern would also be expected to result in an increased complexity. We observe some of these expected changes in Figure 5.

4. CONCLUSIONS & DISCUSSION

We propose in this paper a novel method to calculate local cortical surface complexity without any reference surface model. The quantitative analysis of shape distribution is employed to show changes in complexity in early postnatal neurodevelopment. The stability of the proposed method is indicated by the consistency in local complexity patterns across the 3 studied ages. In contrast to other methods, the presented local measure quantifies complexity at relatively small scale.

It is noteworthy, that the results presented here should be considered preliminary as we chose a constant geodesic kernel size (3mm) for all three ages, whereas the overall brain surface size is increasing over time, as well as different subjects have differently sized brain surfaces. Furthermore, cortical regions would be expected to grown non-uniformly with respect to surface area. This means that the kernel size is not appropriately comparable across different datasets, such as it is chosen either too small or too large. Given the observed sensitivity of the method to the choice of kernel size, an appropriate normalization across subjects as well as along time is thus necessary to compute anatomically valid results. Such a normalization is currently under development in our lab.

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Figure 1.

a) Surface mesh model, b) its shape index map, c) its surface complexity map at a 3mm geodesic kernel. The regions containing both of concave and convex shape show a high complexity values. In contrast, regions of similar shape index show a low complexity score. The range of complexity score is from 0 (blue color; simple) to 0.1 (red color; complex).

Figure 2.

The radius of different geodesic kernels are mapped on the surface model of a 6 month old brain at randomly selected 50 surface vertices. A kernel size below 3mm seems too small to detect valuable local complexity, and a kernel size beyond 4–5mm encompasses both sulcal and gyral regions.

Figure 3.

The validation for different kernel size: a) shows the local shape complexity with each kernel size from 2.5 mm to 4.5 mm and b) employed the heat kernel smoothing with one sigma band width and 100 iteration. Red color means complex and blue color means relatively simple.

Figure 4. Local complexity examples: The local distributions of SI (middle) and its best fitting basic model (right) at selected locations (left). In this particular example, the gyral area (a) shows a higher complexity than the sulcal area (b).

Figure 5.
The local complexity over the age. The gyral area containing concave, convex and branch shape is more complex (red color) than sulcal area relatively (blue color).